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The impact of objective functions on control policies in closed-loop control of grasping force with a myoelectric prosthesis

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Abstract

Objective: Supplemental sensory feedback for myoelectric prostheses can provide both psychosocial and functional benefits during prosthesis control. However, the impact of feedback depends on multiple factors and there is insufficient understanding about the fundamental role of such feedback in prosthesis use. The framework of human motor control enables us to systematically investigate the user-prosthesis control loop. In this study, we explore how different task objectives such as speed and accuracy shape the control policy developed by participants in a prosthesis force-matching task.

Approach: Participants were randomly assigned to two groups that both used identical EMG control interface and prosthesis force feedback, through vibrotactile stimulation, to perform a prosthesis force-matching task. However, the groups received different task objectives specifying speed and accuracy demands. We then investigated the control policies developed by the participants. To this end, we not only evaluated how successful or fast participants were but also analyzed the behavioral strategies adopted by the participants to obtain such performance gains.

Main results: First, we observed that participants successfully integrated supplemental prosthesis force feedback to develop both feedforward and feedback control policies, as demanded by the task objectives. We then observed that participants who first developed a (slow) feedback policy were quickly able to adapt their policy to more stringent speed demands, by switching to a combined feedforward-feedback control strategy. However, the participants who first developed a (fast) feedforward policy were not able to change their control policy and adjust to greater accuracy demands.

Significance: Overall, the results signify how the framework of human motor control can be applied to study the role of feedback in user-prosthesis interaction. The results also reveal the utility of training prosthesis users to integrate supplemental feedback into their state estimation by designing training protocols that encourage the development of combined feedforward and feedback policy.

Introduction

Human hands are extraordinary manipulators supported by a tightly coupled sensorimotor system [1]. They are extremely important both functionally and psychosocially – as our primary means of interacting with the world. Therefore, myoelectric prostheses that aim to substitute for a lost hand have the dual challenge of replacing a dexterous manipulator and the complex sensorimotor substrates that control it.

Sensory feedback plays a critical role in learning and updating the models of interaction between the body and the environment, known as internal models [2]. These internal models allow us to predict how motor commands will change our kinematic/dynamic state and are crucial for forming control policies. Stronger internal models therefore result in 'feedforward' control policies that compensate for the delays and imperfections in sensory feedback as opposed to 'feedback' policies that enable us to make movements in new/noisy environments [3]. Indeed, when learning new motor skills, humans first heavily rely on feedback to accomplish the task goals, however, the feedback is simultaneously used to update the internal models. Once the internal models are acquired, one normally transitions to more feedforward control, and consequently, the movements are performed 'routinely' [4]. The skilled and effortless manner in which we execute movements is most often the result of the combined use of these control policies [5].

After an amputation, the sensorimotor interface between the user and his/her (bionic) limb as well as the dynamic characteristics of the end-effector are substantially altered, but the controller (human brain) and therefore the motor control strategies remain essentially the same. The importance and interplay of feedforward and feedback control processes as well as the role of internal models when interacting with a sensate prosthesis have been recognized in the literature [6], [7]. Consequently, 'supplemental' feedback from the prosthesis to the user has been shown to be beneficial for learning internal models of the user-prosthesis control loop during training [8], [9], for performance improvement in laboratory settings and everyday use [10]–[12], improved embodiment of the prosthesis [13], [14] and to be of user interest [12], [15], [16]. This has led to a growing motivation to provide supplemental feedback in commercial devices (e.g., Vincent Systems GmbH, Mobius Bionics and Psyonic Inc.).

Several methods of providing feedback in upper limb prostheses have been explored ranging from non-invasive solutions such as electrotactile or vibrotactile stimulation, visual and audio feedback, to invasive stimulation of peripheral nerves and cortex [17]–[19]. Furthermore, different variables such as grasping force, closing velocity, and hand aperture were evaluated [20]–[23], with (grasp) force feedback being the most common approach. Some of these methods have shown improvement in performance typically in force-matching task paradigms where participants are asked to produce a given force on an object. Recently, EMG biofeedback [24], [25] and discrete event-based feedback [26] have also shown promising results.

Nevertheless, supplementary feedback remains a somewhat elusive phenomenon, as there are studies showing no benefits of feedback, especially in conditions where intrinsic sources, such as vision and audition, were not blocked [27], [28]. An additional challenge when designing effective feedback is that its impact may depend on multiple factors such as the complexity of the task [12], the amount of training [10] and feedforward uncertainty [6].

As pointed out in a recent review [27], a key missing component to address these challenges might be the lack of knowledge about the behavioral aspects of closed-loop prosthesis control. Most published literature focused almost exclusively on performance improvements, such as increased accuracy or speed in grasp force control driven by supplemental feedback without a formal understanding of how these gains occur. However, a basic understanding of how supplementary feedback is utilized in prosthesis control remains obscure. That is, we still lack an understanding of how the motor control processes such as state estimation and internal models interact with task objectives to give rise to the control policies used during prosthesis control. Elucidating how these processes interact is critically important since supplemental feedback is a component of the overall motor control machinery. Such knowledge would enable us to design feedback interfaces that facilitate the development of specific control policies and/or learning of stronger internal models.

For instance, the grasping force feedback can be exploited in two substantially different manners. During routine grasping, which is particularly relevant for daily life applications, the prosthesis is closed fast around an object [20]. In this case, there is no time for the force feedback to be exploited during grasping, but the feedback can be used to adapt the feedforward commands across trials [10]. On the other hand, during delicate grasping, the hand is closed slowly and the feedback is used to modulate force gradually during ongoing task. The former leads to a feedforward control policy where state estimation is achieved mostly by using (residual) proprioception and other incidental sources of feedback such as vision and audition. The latter, however uses the supplemental force feedback and integrates it into state estimation leading to a feedback policy. While both these approaches to feedback have been indicated before [20], [27], they have never been compared directly.

In this study, we use a force-matching task to understand how specific task objectives affect both performance and behavior in the task, as participants use simple EMG based control and vibrotactile force feedback from the prosthesis. Participants were divided into two groups who used identical control and feedback interfaces but received different instructions on how to perform the task. The instructions defined the objective functions that the participants were supposed to maximize, and the objectives changed during the experiment imposing different tradeoffs between generating desired grasping force and decreasing the time to accomplish the task. We evaluated the success of participants in achieving the given objectives, explored how the objectives affected the control policy (feedback versus feedforward) developed in each case, and compared the performance of the adopted control strategies.

Methods

Participants

Seventeen healthy, able-bodied participants (11 male and 6 females; age: 28 ± 2 years) were recruited. All participants signed an informed consent form before the start of the experiment. The experimental protocol was approved by the Research Ethics Committee of the Nordjylland Region (approval number N-20190036).

Experimental Design

The experiment was conducted over two consecutive days, with the sessions lasting approximately two hours and one hour, respectively. Participants were randomly assigned to two groups, exploratory (EG, 9 participants (5 male and 4 females, age: 29 ± 2 years) and routine (RG, 8 participants (6 male and 2 females, age: 27 ± 3 years)), who received different instructions but used the same control and feedback interfaces. The data from one participant in EG was excluded from further analysis as explained in section Statistical Analysis. While the primary objective throughout the experiment was to reproduce the target force successfully, there were two phases where the participants had different secondary constraints/objectives as shown in Figure 1(C). On Day 1, the participants learned to perform the task according to the differing instructions, and they returned on Day 2 to perform a retention test. The aim of the latter was to assess potential change in performance with and without feedback after a 1-day break, without any further training.

During Phase 1, participants in the EG were instructed to maximize their trial success (reach the target force) without paying any attention to time. Participants in the RG were also asked to maximize their trial success, but with a time restriction, where the hand was automatically opened 1 s after contact. Therefore, they had a limited time during which they received and processed the force feedback, while those in the EG had as much time as they wanted. Hence, the participants in the EG were free to decide on the best strategy to accomplish the task, as there were no imposed constraints. Contrarily, the participants in the RG were "forced" to use a feedforward control policy. They needed to exploit the proportionality of prosthesis response and adjust muscle contraction strength before the hand contacted the object, because there was only 1 s to perform corrections after contact. To the participants in the RG the vibrotactile stimulation essentially transmitted 'end-point feedback' [29] on the task outcome (force applied) which they could use to adapt their EMG commands across trials. The aim of Phase 1 was therefore to investigate the control

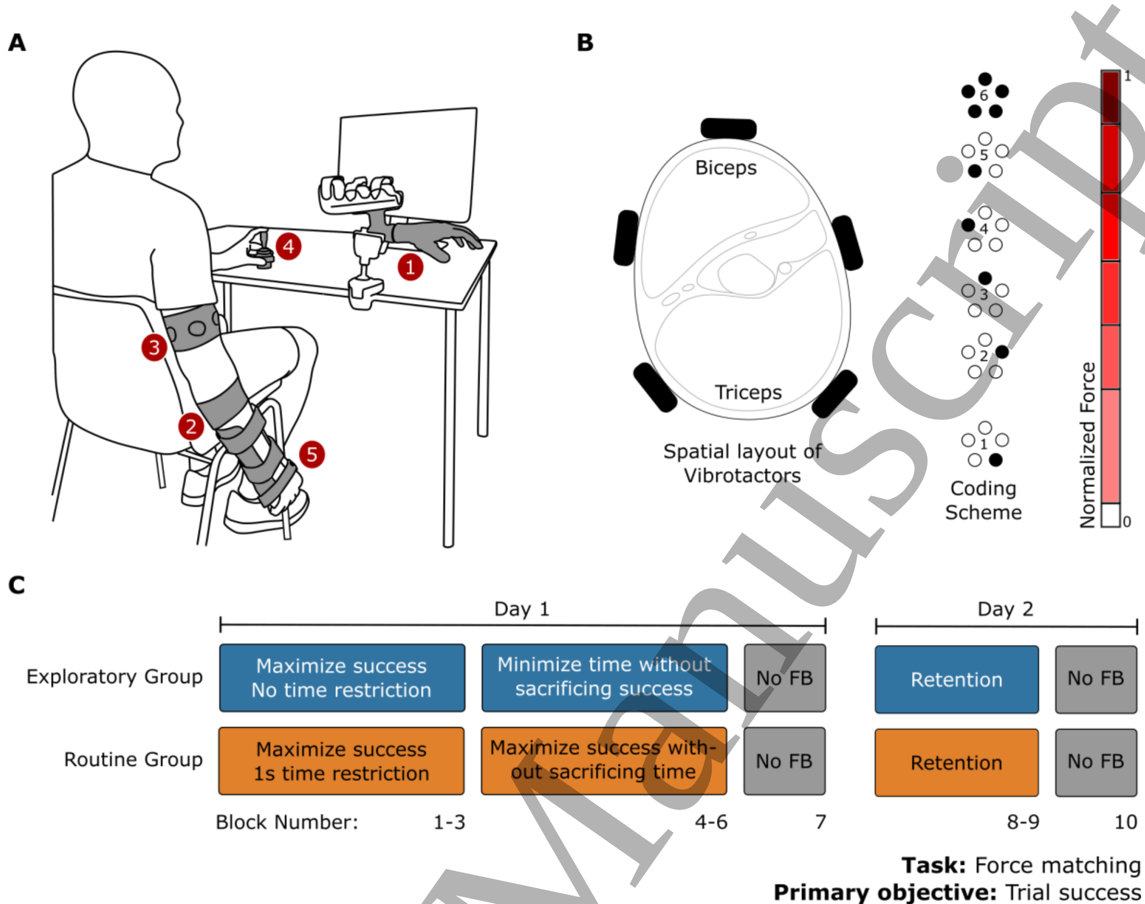

Figure 1 Experimental setup and protocol. (**A**) Sketch of the experimental setup showing 1. Michelangelo prosthesis, 2. OttoBock dry EMG electrode, 3. Vibrotactor array that provided force feedback, 4. Joystick to communicate end of trial and 5. Wrist immobilization splint. (**B**) The arrangement of the vibrotactors around the upper arm (left) and the spatial coding scheme (stimulation patterns) used to communicate the different levels of normalized force (right). (**C**) Experimental protocol for both groups on both days. Note: instructions during retention test are identical to those during blocks 4-6.

policy adopted by the participants in the EG and compare their performance to the feedforward "benchmark" of the RG.

During Phase 2, participants in the EG were asked to minimize the completion time without sacrificing on their trial success. Participants in the RG were instructed to continue maximizing trial success without sacrificing on their completion time; however, they were informed that 1 s time constraint was now removed. Therefore, in Phase 2, we investigated if the EG would be able to perform faster, and whether this would entail a change in control policy or an improvement in the policy that was originally adopted and vice versa for the RG. All participants were asked and encouraged to follow the instructions regarding the trade-off between performance and time, and they were informed that failure to satisfy the instructions did not have consequences such as repeating the experiment until the objectives are satisfied.

Experimental Setup

The experimental setup is shown in Figure 1(A). Participants were seated in a comfortable chair, with an unrestricted view on the prosthetic device (Michelangelo hand, OttoBock, DE) and a 22" computer screen showing task instructions. A single dry EMG electrode with an embedded amplifier (13E200, OttoBock, DE) was placed over the wrist flexors of the right forearm, located by palpating and visually observing muscle contractions. Five vibrotactors (C-2, Engineering Acoustics Inc.) were positioned equidistantly and circumferentially around the upper arm and an elastic band was used to keep them in place. Participants donned a thermoplastic wrist immobilization splint to produce near-isometric wrist flexion and kept their arm in a self-selected comfortable position throughout the experiment. A joystick (2-axis, 1-button) was used to control the end of trials during the task (see Experimental Protocol). The prosthesis was connected to a standard laptop PC through a Bluetooth link, while the vibrotactors and joystick were connected to the same laptop through separate USB ports. The control loop for the experiment was implemented in MATLAB Simulink using a toolbox for testing human-in-the-loop control systems [30] and operated on the host PC in real time at 100 Hz through the Simulink Desktop Real Time toolbox.

Experimental task: EMG Control and Vibrotactile Feedback

The task for the participants was to activate the muscles, close the prosthesis around an object and achieve the desired level of grasping force, while vibrotactile stimulation conveyed the magnitude of the measured grasping force. Participants used near-isometric wrist flexion and proportional control to generate velocity commands to close the prosthesis. Opening the prosthesis was automatic and triggered at the end of each trial. The single electrode was used to record the root mean square (RMS) of the EMG signal, which was sampled at 100 Hz by the embedded prosthesis controller. The signal was further digitally filtered using a second order Butterworth low-pass filter with a 0.5 Hz cutoff. The filtered signal was normalized to 50% of that observed during maximum voluntary contraction (MVC). The prosthesis closing speed as well as the grasping force was proportional to the normalized myoelectric signal (as in most commercial prostheses).

The Michelangelo prosthesis was configured to produce palmar grasps and the force applied on grasping the object (hard sponge wrapped around the prosthesis' thumb) was measured by a sensor embedded within the prosthesis. The measured force, sampled at 100 Hz by the embedded controller, was normalized to the maximum prosthesis force and divided into six discrete ranges (levels) with boundaries at {0, 0.3, 0.44, 0.58, 0.73, 0.88 and 1} on the normalized scale. A spatial coding scheme consisting of six stimulation patterns was used to deliver these discrete levels of force as feedback through an array of five vibrotactors (see Figure 1(B)). The tactors were placed circumferentially and equidistantly on the upper arm around a cross section containing the biceps. An elastic band was used to keep the tactors in place. The first five levels were indicated by activating one of the tactors from the array while the sixth level was conveyed by activating all the tactors simultaneously. If the vibrotactors evoked an unpleasant or poorly localized sensation, their position was adjusted until the participants could easily distinguish all six stimulation patterns (levels). The vibration frequency for all tactors was set to 200 Hz, and the stimulation pattern was updated at 50Hz.

Experimental Protocol

Initially, all equipment (EMG electrode, vibrotactors and splint) were placed on the participant. Then a brief calibration and familiarization followed on both days. On Day 1, a small ink-mark was made on places where the EMG electrode and vibrotactors were placed to ensure that the placement was identical on both days. During the EMG calibration phase, three 5-s long MVCs were recorded and the final MVC value was determined by averaging the three trials. Next, the participants were familiarized with proportional EMG control. To this aim, they were guided to explore how their EMG signal affected the prosthesis velocity (proportional response). Finally, during the familiarization phase for the feedback interface, participants performed a spatial discrimination task where they were presented with two sets of 18 stimulation patterns (3 repetitions for each of the 6 levels, Figure 1(B)) and asked to identify the patterns. The experiment proceeded after ensuring that the participants achieved at least 95% success rate in the discrimination task.

After familiarization with the control and feedback interfaces, the participants were guided to perform 3-5 practice trials of the force-matching task, where the goal was to close the prosthesis and match a target force displayed on the screen. Briefly, each trial began by displaying the target level and the participant was then asked to modulate their muscle contraction and use the force feedback to determine if the target was successfully reached. Once the participants felt they successfully reached (or overshot) the target, they were instructed to relax their muscles and press the joystick button to indicate the end of the trial. Immediately after the trial ended, visual feedback was provided about trial success (a green screen with the message “Well done” for a successful trial and a red screen with “Missed it” otherwise) for 3 seconds before the next trial started. During the practice trials, the participants were explained how to modulate their muscle contraction to control the closing velocity of the prosthesis and how force feedback is delivered after the object was contacted. In this study, we discretized the force sensor readings from the prosthesis into six discrete levels but only used levels 4 and 5 as targets in the task. Two levels were selected to make it easier for participants to learn the task within the short duration of the experiment and mid to high levels were chosen as they are more challenging to reach.

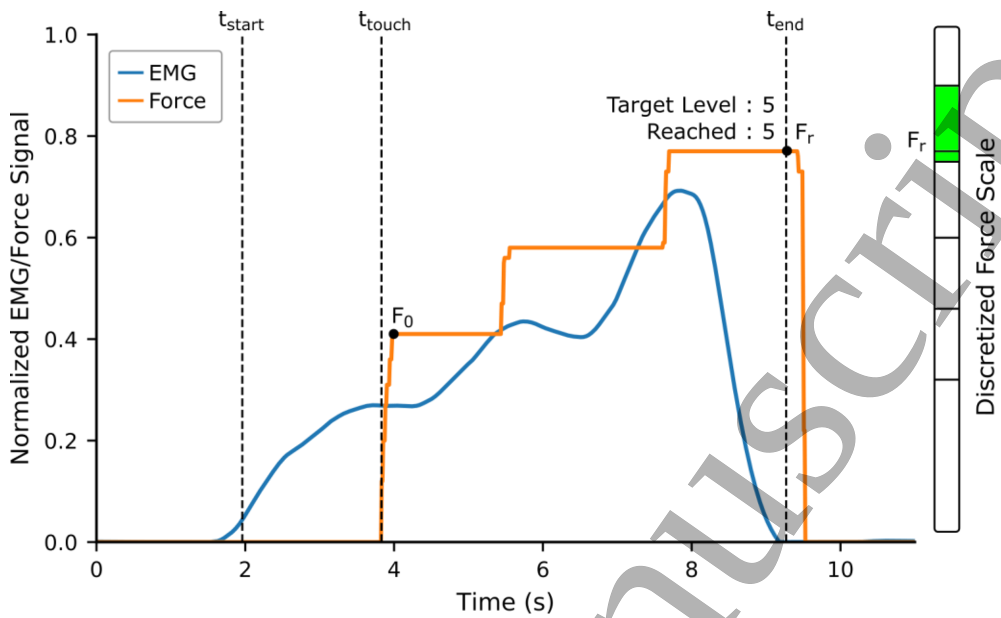

Figure 2: Performance and explanatory outcome measures for one example trial. Normalized EMG envelope (blue line) and force sensor readings (orange line) are used to compute trial outcome ("success") and completion time (7.3s) along with other explanatory variables: (1) time before contact = 1.8s, (2) time after contact = 5.5s, (3) number of corrections = 2, (4) average time per correction = 2.1s and (5) initial plateau force (F_0) = 0.41. The green segment on the force bar (right) indicates the desired force while F_r is the generated force. The vertical dashed line mark the onset of contraction, contact with the object and end of trial.

After the practice trials, the participants performed 7 blocks of 40 trials on Day 1 (blocks 1-7) and 3 blocks on Day 2 (blocks 8-10). The number of blocks differed on the two days since no additional training was required on day 2 (a retention test). In each block of trials, the target forces (4, 5) were presented 20 times each in random order. While the primary objective of the task was to reproduce the target force successfully, participants had different secondary constraints/objectives as shown in Figure 1(C) and explained in section "Experimental Design". The first set of objectives (Phase 1) was presented during blocks 1-3 while the objectives for Phase 2 were presented during blocks 4-6 and 8-9. During blocks 7 and 10, which were the last blocks on Day 1 and Day 2 respectively, the force feedback was deactivated, and the participants were instructed to be as successful as possible, to determine the impact of feedback on performance.

To encourage performance, participants were shown the proportion of successful trials and average completion time per trial, of all blocks until that point, at the end of each block of trials. Note that except during blocks 1-3 for the RG, the end of trial was always communicated by pressing the joystick button.

Outcome Measures

For each trial, the normalized myoelectric signal and force sensor measurements (EMG and force trajectories) were recorded and processed to obtain performance and explanatory outcome measures. Success rate, defined as the percentage of successful trials, and completion time (average, per trial) were calculated for each block as the performance measures. Force reached on a given trial ($\mathrm{F_r}$), (see Figure 2) was computed as the average over the last 100 ms before pressing the button (or the equivalent time before the prosthesis was automatically opened during Phase 1 for RG). The completion time was measured from the point when EMG was at least 3% on the normalized scale ($\mathrm{t_{start}}$) until button press (or hand open, $\mathrm{t_{end}}$, in RG).

In addition, we derived five variables to explain the behavioral differences either across groups or across blocks within the same group. The trial completion time was divided into (1) predictive time (before object contact, $\mathrm{t_{touch}} - \mathrm{t_{start}}$) and (2) corrective time (after contact, $\mathrm{t_{end}} - \mathrm{t_{touch}}$). These two measures enabled us to understand the contributions of predictive feedforward commands in the absence of feedback, and corrective commands generated based on the feedback if the target force was not reached upon contact. Furthermore, (3) the number of corrections made per trial and (4) average time per correction were measured to analyze how participants utilized the feedback to reach the target. Note that after contact, the prosthesis force increased in discrete steps (Figure 2), which is a known characteristic of commercial prosthetic hands (due to, e.g., heavy gearing, non-backdrivability). The number of corrections was therefore calculated as the total number of plateaus in the force trajectory minus one, to discount the final plateau before trial end. Finally, (5) initial plateau force was also recorded to evaluate how far from the target force the participants were upon object contact. An initial force that is farther away from target force would imply that participants relied more on the corrective phase of grasping to reach the target instead of predictively modulating to it.

Trials where the participants did not relax their muscle contraction before pressing the button were excluded from all analyses. Whenever observed doing so in the experiment, the participants were instructed to relax their muscles before pressing the button in order to ensure that force applied on the object would not increase after the termination of the trial. Due to these criteria, 1.3% of all trials were eliminated (with a maximum of 19/400=4.75% trials from one of the participants).

Statistical Analysis

Statistical analysis was performed on performance and explanatory outcome measures at two time points – Block 3 and Block 6, which marked the end of Phase 1 and Phase 2 (on Day 1) respectively. In effect, blocks 1, 2 and 4, 5 were considered as practice blocks in Phase 1 and 2 respectively. Data from one participant in the EG was left out of the statistical analyses for being an outlier (> 3 x S.D from mean completion time, see Figure 3B). Normality of the data was assessed using Shapiro-Wilk's test following which parametric tests were performed when the assumption of normality was satisfied while non-parametric tests were used otherwise. Paired t-tests (Wilcoxon sign-rank tests) were performed to analyze mean differences in performance outcomes across the two time points within the same group. Independent t-tests (Mann-Whitney U tests) were performed to analyze mean differences between the groups at both time points. All statistical tests were performed in R, with the significance level set to $p < 0.05$ for all outcome measures, and a Dunn-Sidak correction was applied to control the family wise error rates (4 tests per outcome variable) for the performance outcomes. Median (M) and interquartile range (IQR) scores per group are reported throughout the paper as M {IQR} unless noted otherwise.

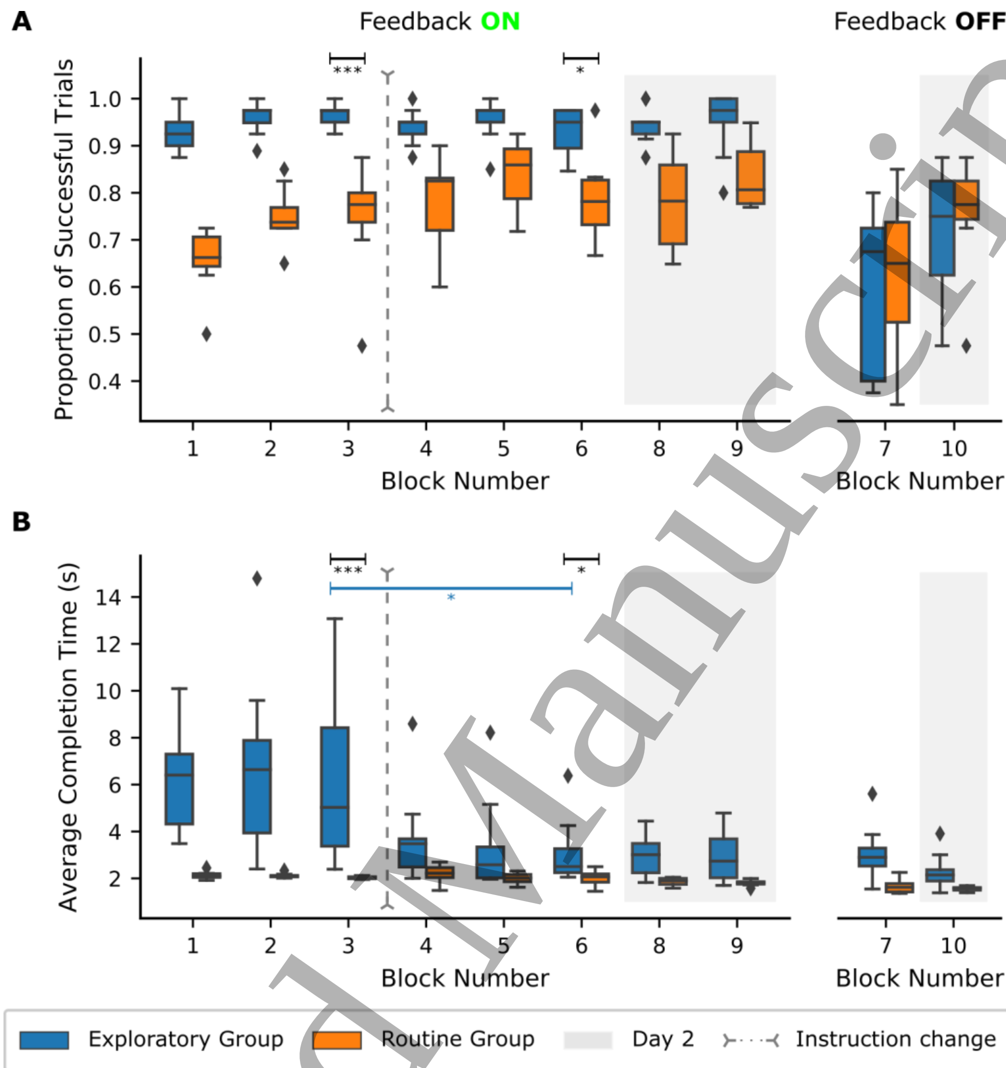

Figure 3: Performance measures. (**A**) Boxplots show the proportion of successful trials per block (success rate) for both groups, plotted across all blocks and divided into blocks with and without the force feedback. (**B**) Boxplots of average completion time per trial (in seconds) across blocks. Horizontal bar indicate statistically significant difference (*, $p < 0.05$; ***, $p < 0.0001$), while diamond shapes are outliers.

Results

Performance Measures

Both groups of participants learned to perform the task with ease and maintained good success rate over the course of the experiment, see Figure 3A. Participants in the EG achieved a high success rate (97% {2%} during Block 3) in Phase 1 (blocks 1 to 3). Participants in the RG tended to improve their performance across blocks but the success rate in Block 3 was still significantly lower (77% {6%}, p=0.0008) compared

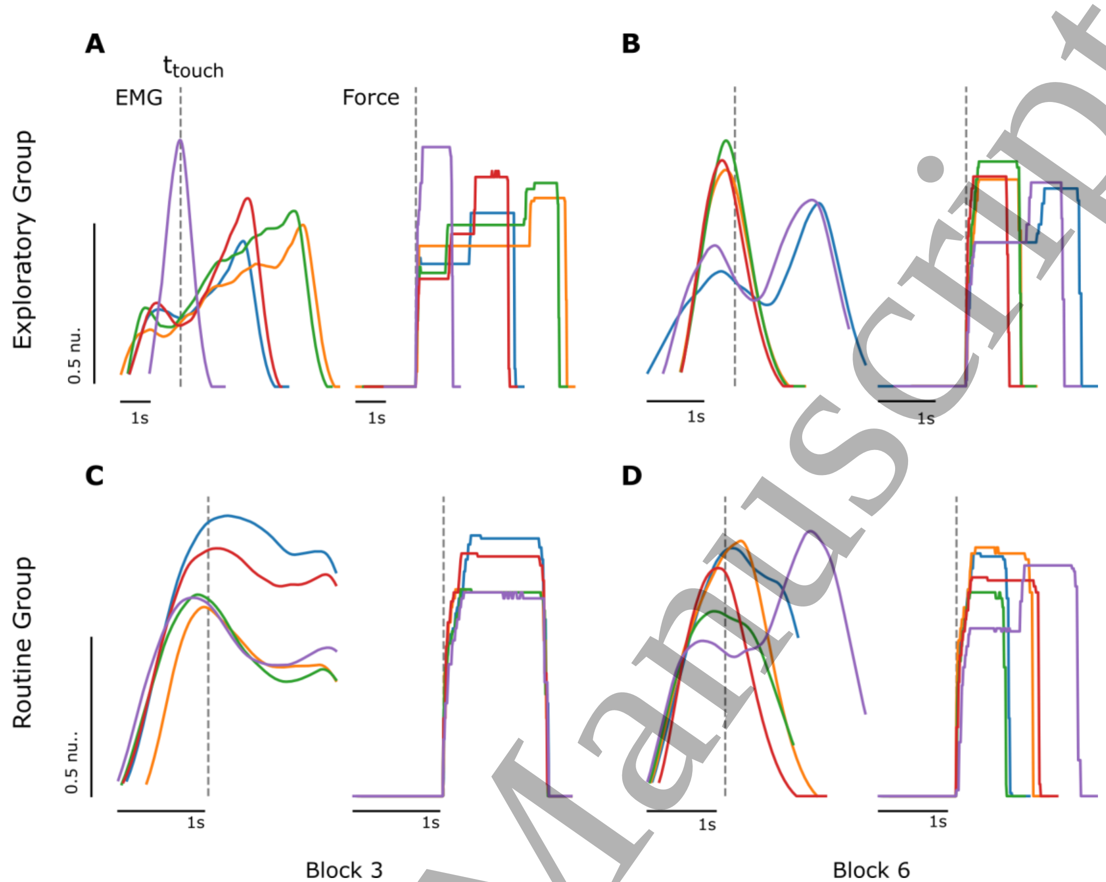

Figure 4: Sample EMG and force trajectories at the end of phases 1 and 2 on Day 1. Each panel shows sample EMG commands generated by one representative participant from each group and the corresponding prosthesis force during a single trial. (A) and (B) depict the trials of the EG participant in Phase 1 and 2, while (C) and (D) are the trials of the RG participant in Phase 1 and 2, respectively. All trials are aligned to the point in time where object contact happens during the trial (t_{touch}). (Note: 'nu.' = normalized units for EMG/Force.)

to the EG. Nevertheless, the EG participants spent substantially longer time to reach the target force compared to the RG (4.6 s {4.7 s} vs 2 s {0.1 s}, p=0.0001, see Figure 3B).

In Phase 2, the participants in the EG did not sacrifice on the success rate (96% {8%}), as indicated by no significant difference between Block 3 and Block 6, exactly as required by the task objective. Nevertheless, they substantially reduced the time to achieve the desired force (4.6 s {4.7 s} vs. 2.4 s {0.9 s} in Block 6, p=0.01). The participants in the RG, however, failed to improve the success rate although the time constraint was removed (79% {8%}), with no significant difference between Block 3 and Block 6. The grasp time also did not change significantly (2 s {0.1 s} vs. 2.1 s {0.3 s} in Block 6, p=0.86). Therefore, in Phase 2, the participants in the EG continued to enjoy significantly higher success rates (96% {8%} vs 78% {9%}, p=0.01) while the time to reach the target force was now much closer to the time achieved by the RG group (2.4 s {0.9 s} vs 2.1 s {0.3 s}, p=0.01). The difference in time was nevertheless still significant.

During the feedback-withdrawn blocks, no significant difference was observed between the groups in success rate but the participants in the RG were faster than those in the EG (1.6 s {0.3 s} vs 2.7 s {0.6 s}, p=0.004). Both groups maintained similar success rates and completion times during the retention tests (with same instructions as Phase 2) on Day 2.

Behavioral Differences

One of the primary aims of the study was to analyze if different objectives during the experiment would lead to the development of different control policies. Figure 4 shows example EMG and force trajectories of one representative participant from each group at the end of both phases on Day 1. During Phase 1 (here Block 3), the participant from the EG closed the prosthesis carefully at low velocity producing a low level of grasping force upon contact. Then, the participant made several corrections of the force to reach the desired level (Figure 4A, right). The EMG profile (Figure 4A, left) reflects this strategy of careful modulations as it contains multiple ripples during its gradual increase. During Phase 2 (Block 6, Figure 4B) however, the same participant adopted a substantially different approach. The EMG commands became smoother, exhibiting one or two peaks, number of corrections of force decreased and the initial force was higher and closer to the target level. In several cases, the participant successfully achieved the desired force right after contact and there was no need for further corrections. Contrary to EG participant, the RG participant did not change strategies between the phases, with most of the trials being completed with a smooth single-peaked EMG trajectory (Figure 4C, D), indicating feedforward control. Therefore, the EMG and force profiles of both the EG and RG participant were rather similar in Phase 2. In summary, these observations indicate that the EG participant started with a feedback-driven control policy, but in Phase 2 also developed feedforward control. On the contrary, the RG participant started with and then maintained the feedforward approach throughout the experiment. Consequently, from the above individual observations we find a distinct emergence (both participants) and change of control policies (only EG participant) between the two phases.

These observations, based on a single participant from each group, are in fact representative of the group as a whole, as demonstrated by the summary results for the explanatory variables. Firstly, we found that the participants in the EG decreased both predictive time (1.5 s {1.4 s} vs 1.2 s {0.2 s}, p=0.07 n.s.) and corrective time (3 s {4.2 s} vs 1.2 s {0.9 s}, p=0.01) between blocks 3 and 6 (Figure 5A). That is, the participants both grasped the object faster and used less time for the modulation of commands after contact. Consequently, we found an increase in the initial plateau force as a direct result of grasping the object faster (Block 3: 0.54 {0.2}, Block 6: 0.67 {0.1}, normalized force units, p=0.01). The number of corrections they

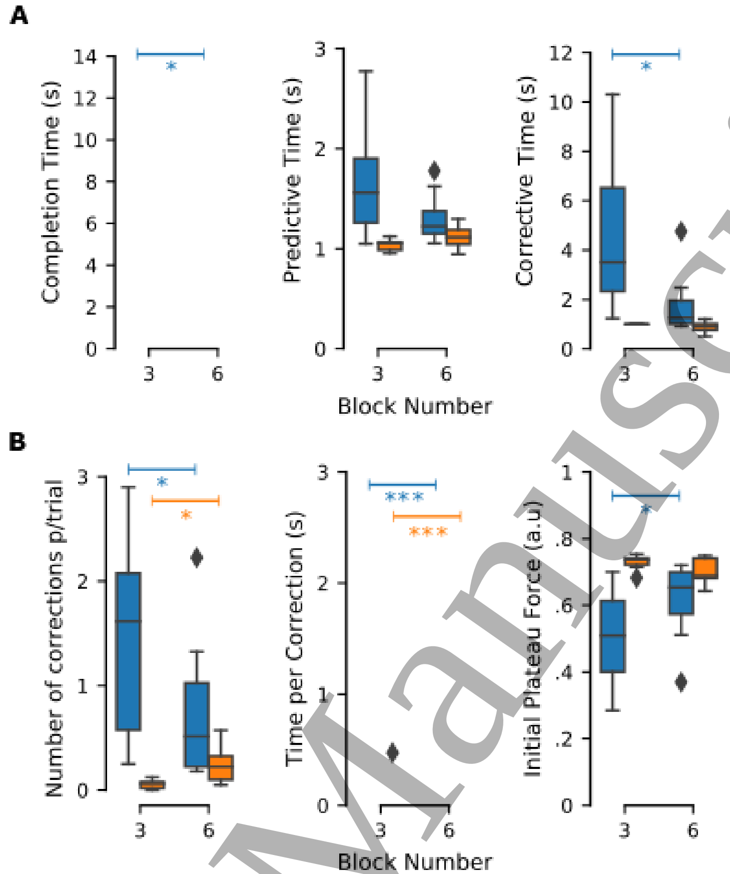

Figure 5: Behavioral differences across groups. (**A**) Differences in completion (left), predictive (middle) and corrective (right) time (in seconds) between phases 1 and 2 for both groups. (**B**) Similar to (**A**), shows differences in the number and duration of corrections, and the average initial plateau force maintained per trial.

made also decreased across the blocks (Block 3: 1.3 {1.5}, Block 6: 0.4 {0.8}, p=0.02). Therefore, in Phase 2, the participants in the EG exploited the proportional response of the prosthesis to incorporate a feedforward strategy. Namely, they realized that they could close the prosthesis faster in order to generate a higher force upon contact, thereby reaching closer to the target force. Consequently, they needed to make fewer corrections after contact (Figure 5B). Taken together, we observe a clear change in strategy from predominantly feedback driven to a combination of feedforward and feedback driven control policy for the participants in the EG. Furthermore, they were also faster in making the required corrections since the time spent per correction decreased significantly from Block 3 to Block 6 (Block 3: 2.1 s {0.7 s}, Block 6: 1.13 s {0.5 s}, p=0.0009). Hence, in Phase 2 not only did the EG participants started using feedforward control but they also improved the efficacy of feedback driven corrections.

In the RG, the behavioral outcomes also changed between Phase 1 and Phase 2, but the differences were marginal. The participants maintained their completion time as instructed, and no significant difference was observed in either predictive or corrective time. However, they slightly decreased the initial plateau force (Block 3: 0.74 {0.02}, Block 6: 0.69 {0.06}, p=0.06 n.s.) and increased both the number of corrections (Block 3: 0.06 {0.06}, Block 6: 0.2 {0.2}, p=0.01) and time per correction (Block 3: 0.6 s {0.03 s}, Block 6: 0.9 s {0.33 s}, p=0.007). While the participants decreased the initial plateau force and made corrections on some trials during Phase 2 (Figure 5B), this strategy did not affect the overall success rate and completion time (see section above). This therefore indicates that the participants in the RG used a predominantly feedforward control policy in both phases.

Discussion

In this study, we developed an experimental paradigm to explore how task objectives influence the control policies employed by the participants in a force-matching task using a myoelectric prosthesis equipped with vibrotactile feedback. Participants in the EG, were first instructed to disregard the amount of time they take to reach the target force level and then to try to improve on their speed. On the other hand, the RG started with a time constraint that was later removed. Thereby, the EG were initially free to develop whichever control policy they wished, while the RG were forced to develop a feedforward policy. We then investigated if and how these policies changed upon changing the task objectives.

Phase 1: Emergence of distinct control policies

Firstly, we observed during Phase 1 that participants in the EG achieved a high success rate. However, the high performance was achieved at the expense of rather slow grasping. The participants slowly modulated their commands during both predictive (before object contact) and corrective (after contact, when force feedback was available) phases of grasping and made careful corrections in the force level after contact. Together, these indicate that the EG participants used a feedback control policy during Phase 1. Participants in the RG developed a feedforward control policy and achieved a significantly worse success rate in Phase 1. This was corroborated by the brief predictive time leading to an initial plateau force close to the target force and no corrections in force level. While similar behavior was observed in previous studies that used the routine grasping task paradigm [20], [28] here we contrast it to the behavior exhibited when using a feedback control policy.

Our results highlight the differences between two potential ways of using supplemental feedback: online modulation (EG) and adaptation (RG). In the latter, the vibrotactile stimulation provides end-point feedback (i.e., trial outcome ~ generated force), which is then used to correct the feedforward command in later trials. While the RG participants improved their success rate across blocks, they could not reach the performance of the EG participants, even though the task was limited to producing two target force levels. This points to a potential intrinsic limitation in the "pure" feedforward approach, related to feedforward uncertainty [6]. The latter limits how well the participants can reproduce similar levels of muscle contraction across trials as well as maintain that contraction within the trial. In other words, the feedforward strategy produces a fast grasp but unavoidably penalizes accuracy and leads to limited improvement, especially during short-term training. Nevertheless, this strategy has been shown to be useful if the controlled system has a reliable response and the task is simple [6], [8].

Phase 2: Flexible adaptation versus rigid maintenance of control policy

During Phase 2, the participants in the EG reduced their completion time dramatically without sacrificing on success. Interestingly, while they could have decreased the time by simply optimizing the execution of the same control policy (faster feedback modulations), the results show that they made improvements in both predictive and corrective phases of grasping. During the predictive phase, they were faster and reached a higher initial plateau force such that in the corrective phase they mostly made a single correction in force to reach the target (Figure 5). Therefore, the participants ended up using a combination of feedforward and feedback policies. The participants adapted to a different task objective by flexibly changing the control policy, and they have done this almost immediately, i.e., already in the first block of Phase 2 (see Figure 3). They readily exploited the prosthesis proportional response and natural feedback from the muscles (sense of contraction) to engage in predictive control, although this has not been explicitly practiced during Phase 1.

Contrarily, participants in the RG did not attain similar improvements in their success rate and they maintained a predominantly feedforward control policy as reflected by no significant change in predictive and corrective time, and the number of corrections. Since the RG participants practiced predictive control from the beginning, we have expected that they will introduce some level of feedback control after corrections were enabled by removing the time limit. For instance, one strategy could be to aim intentionally at the level below the target and then 'correct'. This could have improved the success rate while minimally affecting the time. However, it seems that the participants in the RG had developed a less flexible control policy than those in the EG and they simply continued to use the same strategy after the time limit was removed. This might be because they did not practice corrections in Phase 1 and were hence reluctant to rely on those in Phase 2. Therefore, it seems that the transition from feedback to feedforward strategy was more natural (EG) compared to introducing some feedback into feedforward policy (RG).

Finally, we expected that the focus on purely feedforward control in the RG would prove beneficial when the feedback is deactivated. However, this was not the case. It seems that in phase 2, the EG participants adopted enough feedforward control, assisted potentially with some intrinsic prosthesis feedback (e.g., an auditory/kinematic cue when changing the force), to perform as well as the participants from the RG when the feedback was removed.

Implications for training and experimental design

Overall, in this experiment, we used the framework of human motor control and built on earlier work on feedforward and feedback processes in the human-prosthesis control loop [6] to understand how task objectives determine the developed control policy. We demonstrated that neither purely feedforward nor feedback-driven strategy is an optimal approach to prosthesis control with force feedback, but a policy that combines the two. In Phase 2, the EG participants, who used the latter approach, maintained significantly higher success rates while closely approaching the completion time achieved by the RG. The RG, on the other hand, did not approach the success rate of the EG despite the training in Phase 2.

The variability of completion times observed in the RG group is smaller compared to the EG. This further highlights the constrained nature of the task the RG participants were performing in Phase 1 (grasping with the time restriction), and the rigid control policies they have thus developed in Phase 1 and 2. On the contrary, variability of completion times for the EG participants in Phase 1 was large, indicating that participants explored different strategies across trials (slower and faster grasps) in order to maximize their accuracy. Such exploration has presumably facilitated the transition from mostly feedback driven (Phase 1) to the combined feedback and feedforward strategy (Phase 2) in the EG group. This transition is also marked with a drop in variability in Phase 2 as a soft time restriction (instruction to be faster without sacrificing accuracy) was introduced. Together, these results explain the role of speed and accuracy constraints on performance outcomes, and serve as a guide for designing future experiments. In addition, our results highlight the advantages of first developing a feedback policy that might result in stronger internal models due to greater exploration of how to produce the desired movement. These insights imply that rehabilitation protocols for the training of closed-loop prostheses control should focus on the development of combined feedback and feedforward control policies starting first with (mostly) feedback-driven approach. In addition, the present study demonstrates a clear connection between task objectives and control policies in the context of sensate prostheses, and this speaks for the development of novel experimental protocols testing different objectives in the same task during laboratory assessments as well as clinical applications to further understand how supplementary feedback is used.

Another important observation from this study is the amount of time spent by participants to correct from one level to the next. On some trials, participants in the EG spent up to 3.8 s (95^{th} percentile) on a single correction even on Day 2. This behavior likely reflects the well-known nature of prosthesis force modulations, where in response to a continuous and gradual increase in muscle activation, the force changes suddenly and in discrete steps (due to the gearing mechanism in the prosthesis, [20], [31]). Combined with the noisy sense of muscle contraction, especially at higher intensities [32], this makes it difficult for the participant to predict when and by how much the force would increase. However, it seems that on average, the participants in the EG were able to learn how to compensate for this drawback, as the average grasping time has decreased substantially in Phase 2 and approached that of the RG group. The RG participants did not face this limitation, because the desired force was produced right after contact (no corrections). Apart from practice, this could be also addressed by providing continuous EMG biofeedback [24], which would convey more detailed information to the user about the degree of activation within each level and thus what change in muscle activation is required to reach the next level. More generally, the EMG biofeedback [24], [25] can also be used to facilitate participants to modulate their commands predictively, which might be beneficial particularly for the RG participants.

Limitations and outlook

A limitation of the present study is the absence of amputee subjects. The amputation might affect myoelectric control signals (both patterns and strength) and/or skin sensitivity, and the performance may depend on the level of previous experience with a myoelectric prosthesis. However, our experimental assessment relied on simple control (single muscle), task (1-DoF) and feedback encoding (spatial scheme), while myoelectric signals were normalized to the MVC of each participant. Therefore, we expect that the results would be similar in amputees, especially in naïve subjects that are new to prosthesis use and myoelectric control; nevertheless, it remains to be experimentally verified.

The present study used simple direct proportional control as it was sufficient for the 1-DoF task, namely, the control of prosthesis closing and grasping force. In addition, this approach still remains the clinical standard. Nevertheless, myocontrol based on pattern classification, which has recently been made commercially available, shows significantly improved performance and user satisfaction [33], [34]. It is therefore an important future goal to investigate the impact of task objectives on the control policies when feedback is combined with more advanced control. The choice of the control scheme is expected to become particularly relevant when the sensate prosthesis is used to perform more complex tasks (e.g., multi-DoF control).

Future studies should be conducted to explore how supplemental feedback can be used in complex functional tasks under changing objectives. While feedback has already been shown to be more useful in difficult tasks [12], [17], it remains to be seen if explicit training of combined feedback and feedforward policies would affect performance and 'embodiment'. Future clinical work would also benefit from training users to explore different objectives in a given task and understanding how coaching can play a complementary role in such explorations.

Conclusion

This study explored the development of control policies in face of changing task objectives. By manipulating the speed and accuracy demands in a simple force-matching task with a sensate myoelectric prosthesis, we demonstrated that the participants used grasp-force feedback successfully within and across trials to train both feedback and feedforward control policies. We further showed that change in objectives led to an immediate change in feedback but not in feedforward policy. Overall, the results indicated that a) the use of feedback for online modulation versus inter-trial adaptation both exhibited important drawbacks, b) the overall best approach was a strategy combining feedforward and feedback control policy, and c) such integration was best achieved by training the feedback control first.

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